Title: The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services?

Running Title: A perspective built by extending the Meta-UTAUT framework

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Abstract

The growing usage of chatbots in the service industry indicates the ongoing transformation occurring in this sector. However, minimal research has (i) investigated the important attributes related to chatbot-based service continuance intention and social self-efficacy. This study proposed an extended meta-UTAUT framework to investigate the gaps by including perceived intelligence and anthropomorphism (system factors) in the model. The model is analysed using structural equation modelling with 420 respondents. The study results indicated that perceived intelligence and anthropomorphism are more related to building attitude and continuing intention of using chatbot-based services than traditional meta-UTAUT constructs. Furthermore, the model results demonstrated that system factors are negatively associated with continuation intention when interactive with social self-efficacy. The study results extend the theoretical knowledge available in meta-UTAUT, technology-based services, and social cognitive theory. In addition to the academic contribution achieved, the study results develop insights into service practices for IT managers.

Keywords: meta-UTAUT; chatbot based services; perceived intelligence; perceived anthropomorphism; continuation intention; social self-efficacy

1. Introduction

The use of chatbots in the services industry is one of the significant advancements in recent years (Balakrishnan and Dwivedi, 2021a). A chatbot is a computer program that conducts a conversation in natural language and sends a response based on business rules and data tuned by the organization (Balakrishnan and Dwivedi, 2021a; p. 3). Compared to other information communication technologies (ICTs), chatbots employ intelligent cognitive frameworks to simulate an improved response to customer queries (Balakrishnan and Dwivedi, 2021b). Recent studies are more diversified and address the challenging aspects of adopting these intelligent cognitive frameworks (Duan et al., 2019). The use of chatbots has become omnipresent across every stage of marketing (i.e.), pre-purchase, purchase, and post-purchase, with service engagement being present in every step of the purchase funnel (Mishra, 2020). The growth of chatbots has drawn the attention of both industry and academia. Recent studies have attempted to connect various theoretical frameworks such as; the technology acceptance model (Balakrishnan and Dwivedi, 2021b), expectation confirmation theory (Eren, 2021), cognitive absorption (Balakrishnan and Dwivedi, 2021a), service quality dimensions (Meyer-Waarden et al., 2020), status quo bias (Balakrishnan et al., 2021), to develop improved understanding of the factors that can build intention to use chatbots. Prior studies have typically considered the use of chatbots from a user perspective with minimal consideration on how the system factors present in chatbots have contributed to the behaviour. Similarly, prior research has investigated the variables and their effect on behavioural intention and intention to use (Wang et al., 2021; Gursoy et al., 2021). However, there is minimal understanding given to understanding these chatbots' attitudes and continuing intention with particular reference to services (Sung et al., 2021).

Despite the success of chatbots, research has questioned the use of chatbots in the service industry, given their role as a replacement to social expectations (Hill et al., 2015). Prior studies have queried whether chatbots might not replace human social skills. For example, Croes and Antheunis (2021) found that human's social progression decreased with social chatbots. Human perception (user factors) is among the major factors that drive the success of the information systems (IS) based technologies (Collins et al., 2021). In case of service chatbots, besides the prevalence of user factors, the intelligence and enhanced interaction opportunities with artificial intelligence (AI) integration (system factors) makes chatbots more noticeable (Balakrishnan and Dwivedi, 2021b). Considering the role of using chatbots in services marketing, no existing study has provided a holistic framework to connect users and system factors as moderated by social self-efficacy. Social self-efficacy explains people's belief regarding their level of ability to perform a given task or behaviour in social relationships successfully (Gecas, 1989). Given the rise of technology and people's interaction with cutting-edge technologies, these interactive technologies' social expectations remain at the crossroads (Croes and Antheunis, 2021). Chatbots can be optimised in a functional way through self-learning algorithms (Mogaji et al., 2021), although from a theoretical lens it is necessary to observe the effect of user factors, system factors, and social self-efficacy. In summary, (1) we propose extending the meta-UTAUT framework comprehensively by combining both user (Dwivedi et al., 2019) and system factors (Bartneck et al., 2009; Balakrishnan and Dwivedi, 2021b) to understand their effect on attitudes and continuation intention of chatbots in services. (2) This study introduces social self-efficacy (Gecas, 1989; Wei et al., 2005; Yang et al., 2016) as a moderator in the above relationship. Thus, the study investigates the impact of user factors (meta-UTAUT), system factors (Bartneck et al., 2009; Balakrishnan and Dwivedi, 2021b), and social self-efficacy on users intention to continue with chatbots for services. The following research questions are proposed from the discussion and study objectives.

RQ1: What is the relationship of user and system factors present in chatbots to attitude and continuation intention of chatbots in services?

RQ2: Does social self-efficacy inhibit the relationships proposed in RQ1?

The study results will contribute both from academic and industry perspectives. First, this research extends the UTAUT framework with system factors (perceived intelligence and perceived anthropomorphism) that investigate human-computer interaction (Venkatesh et al., 2003; Dwivedi et al., 2019; Ye, Zheng, and Yi, 2020; Arfi et al., 2021). Second, introducing social self-efficacy as a moderating factor in the framework would contribute novel insights regarding how social relationship expectations can be crucial in technology-driven services. The proposed hypotheses can strengthen the existing knowledge available in social self-efficacy, services marketing, and chatbots usage. Third, Dwivedi et al. (2019) emphasised the importance of investigating the attitude as an outcome of UTAUT, and Sung et al. (2021) stressed investigating the continuing use rather than only investigating behavioural intention. So this study has addressed both the substantial gaps to provide increased knowledge regarding human-computer interaction. Fourth, the growth of technology has impacted various consumer segments; considering this point, to the study seeks to understand how these hypotheses can differ across age and gender variables.

2. Theoretical Background

2.1. User factors (meta-UTAUT)

The emergence of various IS research theories have provided a pluralistic approach to IS researchers to integrate and extend novel research outcomes. The Technology Acceptance Model (TAM; Davis et al. 1989) is considered a seminal theory that have laid a platform for IS researchers to build their propositions accordingly. Whilst Venkatesh et al. (2003) proposed a unified theory of acceptance and use of technology (UTAUT) which introduced and investigated the role of performance expectancy, effort expectancy, social influence, and facilitating conditions to behavioural intention. Though researchers therein mostly used both TAM and UTAUT with equal importance to propose their theoretical underpinnings and derived contribution through this lens (Oliveira et al., 2014; Mortenson and Vidgen, 2016; Patil et al., 2020). However, other studies critically evaluated and suggested areas of improvements in UTAUT models (Patil et al., 2020).

One of the major limitations proposed by Dwivedi et al. (2019); the meta-analytical framework reinstated the importance of introducing "Attitude" in the major UTAUT frameworks. Dwivedi et al. (2019) re-examined the UTAUT basic framework with data from 162 studies comprising 1600 observations; the authors used the MASEM (meta-analysis structural equation modelling) technique to build a comprehensive view of the UTAUT frameworks. Dwivedi et al. (2019) initiated a new outlook for the UTAUT model after finding the significant role of "Attitude" in the framework. This framework (meta-UTAUT) has received equal importance similar to the TAM and UTAUT models. Previous studies have used Meta-UTAUT in various contexts, such as; mobile banking and payments (Patil et al., 2020; Jadil et al., 2021), AI integrated customer relationship management (CRM) systems (Chatterjee et al., 2021), and tourism adoption (Tamilmani et al. 2020). However, given that current research is significantly embarking on seeking understanding of the various functions of chatbots, the comprehensive picture of meta-UTAUT is yet to be examined in the context of chatbots in the services industry. This research uses the five significant meta-UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, and attitude) to identify how it instils to create continuation intention to use chatbot services.

2.2. System factors (extended meta-UTAUT)

Given the functionality of chatbots, previous research has reiterated the use of intelligence and anthropomorphism that is present with the system of chatbots (Balakrishnan and Dwivedi, 2021b). Bartneck et al. (2009a) introduced two essential attributes: perceived intelligence and anthropomorphism as an integral part of AI-based robotic functions. Few prior studies have used these variables. Notably, Balakrishnan and Dwivedi (2021b) investigated the role of these variables in building attitudes towards voice assistants. Perceived intelligence can be explained as the intelligence capability a system can exhibit to perform an action or accomplish an objective (Bartneck et al., 2009b). The intelligent frameworks in conversation-based systems have existed for approximately decade (Dwivedi et al., 2017; Janssen et al., 2018). IBM Watson intelligent systems are a good example of an AI-based intelligent system used in chatbots. Akter et al. (2019) explain that AI algorithms planted in chatbots can develop human-like intelligence. Chatbots or personal assistants are mostly known for their intelligent architecture created to have a productive conversation with users (Moussawi et al., 2020). The intelligence inherited within chatbots builds a wider scope of consumer interaction across their consumer decision-making stages (Parise et al., 2016). Besides intelligence, anthropomorphism is another important attribute that provides increased novelty and appeals to voice assistants. Anthropomorphism at the human-computer interface involves both hardware (physical replication) and software features (internal replication) which triggers an anthropomorphic design (Qiu and Benbasat, 2009). Anthropomorphic features or characters are objects and imaginations that projects human-like characteristics. Recently, anthropomorphic features have been more evident across digital assistants and chatbots (Balakrishnan and Dwivedi, 2021b). Anthropomorphism in chatbots provides a human context that projects the potential conversation in a more human-like manner (Bartneck et al., 2009b). Though businesses incorporate various mechanisms to build chatbots with a human perspective, it is important to understand how consumers perceive anthropomorphic designs. Despite prior research emphasising the role of intelligence and anthropomorphism in chatbots, scholars have yet to extend these attributes from a theoretical lens. Thus this study extends the meta-UTAUT framework by considering these variables.

2.3. Social self-efficacy

Social cognitive theory (SCT) (Bandura, 1989) and the theory of self-efficacy (Bandura, 1977) provide two different doctrines that formulate human behaviour. Self-efficacy is a holistic theory's evolutionary outcome, namely, social learning theory (SLT) (Bandura, 1969). Later progressed to form social cognitive theory. The underlying propositions in SLT and SCT explain that individuals learn to process their cognitive, personal, and environmental factors to determine motivation and behaviour (Crothers et al., 2008). In contrast to SLT and SCT, self-efficacy theory explains that one's belief to accomplish a task can be self-motivating (Bandura, 2012). While SCT is a composition of various factors associated with the broader cognitive spectrum, self-efficacy is an integral component of it, so does social self-efficacy. Social self-efficacy describes a person's ability and belief to perform the task in a social environment (Gecas, 1989). An individual with higher social self-efficacy can accomplish a job in a social environment rather than only depending on their self-beliefs (Sherer and Adams, 1983; Smith and Betz, 2000). While several studies support the importance of social self-efficacy to accomplish any tasks in a social environment, the group of studies purport that a person with higher social-self efficacy can expect (Sherer and Adams, 1983; Smith and Betz, 2000) and entreat to create a new relationship in a given social environment (Gecas, 1989; Jeong and Kim, 2011). Social self-efficacy is primarily investigated in students' social learning (Rosenstock et al., 1988) and social media environment (Yamamoto et al., 2017). Though previous studies have supported the social aspects of the services industry, no study has explored the concept of social self-efficacy in terms of self-service technology or voice agents/chatbots. Imagine a scenario in which a consumer is engaging with a chatbot, the social expectations can influence the complete interaction of the consumer with the chatbot. The same is reflected in this study from an interaction perspective. This study introduces social self-efficacy as a moderator in the meta-UTAUT model to understand how it interacts with the user and system factors to behave with continuation intention to use chatbots. The study model is given in Figure 1.

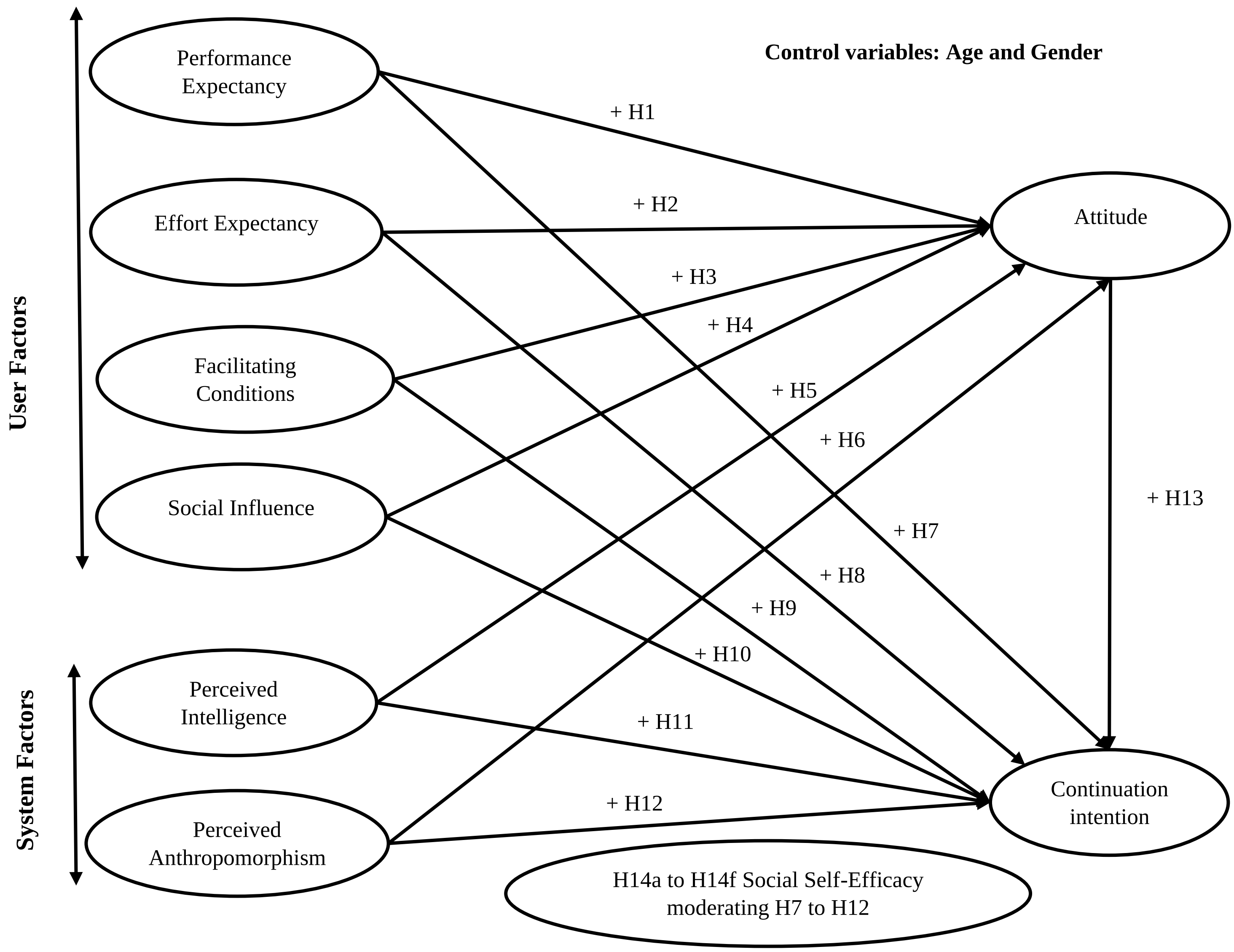

Figure 1: The conceptual model of the study

3. Hypotheses development

3.1. User factors to attitude

Performance expectancy is considered an essential measure in the UTAUT framework (Venkatesh et al., 2003; Patil et al., 2020). Performance expectancy explains the user's benefits while acting on information systems (Venkatesh et al., 2003; Patil et al., 2020). In the meta-UTAUT framework (Dwivedi et al., 2019), the authors found performance expectancy as the most significant variable that builds a favourable attitude in IS research. In mobile payment services, Park et al. (2019) found perceived benefits prevailing in technology interface can create a positive attitude towards technology. The following hypotheses are proposed based on the previous discussion.

Hypothesis 1 (H1): Performance expectancy is positively related to attitude towards chatbot service interactions

Effort expectancy is the other crucial variable that builds behavioural intention towards the technology (Patil et al., 2020). Effort expectancy specifies the degree of easiness connected with the technology (Venkatesh et al., 2003). The consumer value framework supports that marketers tend to build more substantial value for their goods and services by either building more benefits or controlling the costs, in which effort is one of the reflections of costs (Holbrook, 1999). The same principle applies to services, in which marketers attempt to reduce the effort to garner increased value, which can build a positive attitude towards the brand (Kamboj et al., 2018). Thus the following hypothesis is proposed.

Hypothesis 2 (H2): Effort expectancy is positively related to attitude towards chatbot service interactions

Dwivedi et al. (2019) found that social influence is significantly related to attitude in terms of IS research. Social influence can be explained as the degree to which the consumers value the social importance of using a particular technology (Verma and Sinha, 2018). Most studies have found that social influence can significantly build positive behavioural intention towards a specific technology (Alalwan et al., 2018), but not many studies have empirically proposed the role of social influence in creating a positive attitude. Wood (2000) suggested that persuasion and social influence have a stronger influence to build favourable/unfavourable attitudes and ensuing attitudinal change. The same is evident in marketing literature studies. Thus from the above discussion, the following hypothesis is proposed.

Hypothesis 3 (H3): Social influence is positively related to attitude towards chatbot service interactions

Facilitating conditions refer to the needs and support available to perform an action, as perceived by the consumer (Venkatesh et al., 2003). Previous studies in ISs have found facilitating conditions as a significant predictor of behavioural intention (Patil et al., 2020). In the context of services, chatbots can be broadly included under the term "Digital landscapes" (Modgil et al., 2021). Digital landscapes replace physical evidence or service landscape with a virtual environment (Algharabat et al., 2017). Previous studies have found that mobile banking services can build a more robust customer attitude (Sahoo and Pillai, 2017; Gutierrez et al., 2019), but the same has to be explored in the context of chatbots. Thus facilitating conditions can build a stronger attitude towards chatbots. The following hypothesis is proposed based on the above discussion.

Hypothesis 4 (H4): Facilitating conditions is positively related to attitude towards chatbot service interactions

3.2. System factors to attitude

Perceived intelligence in a system denotes a combination of intelligent quotient and capability as decoded by the users. Balakrishnan and Dwivedi (2021b) found that perceived intelligence in voice assistants can build a positive attitude. However, no research has formulated a similar hypothesis in the setting of service chatbots. Previous research has supported that enhanced capability provided in an IS system can develop attitude (Rezvani et al. 2017a). Duan et al. (2019) stated that the intelligent frameworks in the AI interface could motivate the end users to accept the system. Collins et al. (2021) emphasised a similar view, and they offered insights on how intelligent architectures can be strategised to build positive consumer acceptance and attitude. The following hypothesis is proposed from the above discussion.

Hypothesis 5 (H5): Perceived intelligence is positively related to attitude towards chatbot service interactions

Anthropomorphic features denote human-like characteristics incorporated in non-human objects, including voice conversations. Previous research has found that anthropomorphic features have received a good reception from consumers (Lim et al., 2021). However, no study has directly found the impact of anthropomorphism and attitude towards service chatbots. Notably, Martin et al. (2020) found anthropomorphic integration in AI trip advisors positively influencing travellers’ attitude. Moreover, Balakrishnan and Dwivedi (2021b) found that digital assistants' intelligence can build a positive attitude. Anthropomorphism is an object interface that can instil favourable and unfavourable attitudes. Social psychology research posits that any impression of an object with explained characteristics can build attitude (Ledgerwood et al., 2018). From the above discussion, the following hypothesis is proposed.

Hypothesis 6 (H6): Perceived anthropomorphism is positively related to attitude towards chatbot service interactions

3.3. User factors to continuation intention

As mentioned previously, performance expectancy denotes the usefulness and benefits that consumers perceive from a system. Rezvani et al. (2017b) support that benefits in IS from B2B and B2C strategic systems can build a long-term perspective. Nevertheless, any IS research equipped with future performance can yield a long-term association with the system (Duan et al., 2019). In addition, previous research has found that performance expectancy can build continuation intention (Tam et al., 2020), but not directly in the chatbot perspective. In case of chatbots, the depth in interaction between the computer and the machine can objectively enhance the perceived performance, thus can instil continuing intention among the users. Thus from the above discussion, the following hypothesis is proposed.

Hypothesis 7 (H7): Performance expectancy is positively related to continuation intention to use chatbot service interactions

The perception of effort expectancy is deduced based on the easiness prevailing in the system. Previous research has supported that effort expectancy can build a long-term connection with a defined plan (Filieri et al., 2020). Effort reduction is a part of the value chain process that demands marketers and IS people to work together to gain a long-term orientation. Value-based frameworks have suggested that consumers perceived value has a positive relationship with the continuation intention (Gong et al., 2020). In the case of chatbots, AI-based algorithms or simulated environments provides increased preciseness in conversation (Mogaji et al., 2021), reducing the perceived efforts. Thus, the same can yield long-term orientation from the users. Chatbots are effective alternatives to human services, reducing the user efforts objectively, can result in long-term association with the service chatbot. From the above discussion, the following hypothesis is proposed.

Hypothesis 8 (H8): Effort expectancy is positively related to continuation intention to use chatbot service interactions

As discussed in the previous hypothesis, perceived value can build long term orientation. Social influence adds up to social value. However, can the social value create continuation intention among chatbots? Kim et al. (2008) compared the important variables that contrast a difference between discontinuers vs continuers. The survey finding supported social influence as a significant variable that builds continuing intention. However, the study was posited from the perspective of mobile data services. Nevertheless, Lu (2014) emphasises that social influence is a prospective variable that marketers should consider. Chatbots do build a continuing relationship. Thus from the above discussion, the following hypothesis is proposed.

Hypothesis 9 (H9): Social influence is positively related to continuation intention to use chatbot service interactions

Bhattacherjee et al. (2008) illustrates that a user who climatises to an improved facilitating condition in an IS system may continue to use the system. Previous research has found facilitating conditions as a significant variable associated with continuing intention, but not in the context of service chatbots. Apart from ISs, investigations related to retailing confirms the significance of facilitating customers to make them visit again. Chatbots facilitate functional conditions (Mogaji et al., 2021), which can eventually build a case for users to continue using chatbots. From the above discussion, the following hypothesis is proposed.

Hypothesis 10 (H10): Facilitating conditions is positively related to continuation intention to use chatbot service interactions

3.4. System factors to continuation intention

Ashfaq et al. (2020) evaluate chatbots as an intelligent evolutionary system that can build continuing intention to use. Service chatbots equip multi-intelligent frameworks that can allow for productive and precise conversation with the users (McLean and Osei-Frimpong, 2019). The same also pertains to the transformative ability of chatbots. Shim and Jo (2020) state that from a transformational perspective, intelligent systems provide enlarged benefits that can build positive intention to continue with the services. Given the nature of AI and its self-learning transformative features (Montes and Goertzel, 2019), chatbots can cater to the updated requirements of the users. The users can perceive the same during their interaction with chatbots. Chatbots can self-learn based on a defined environment and thus respond or interact appropriately, similar structures can motivate users to continue using chatbots for services. However, this is a hypothetical statement which requires investigation. From the above discussion, the following hypothesis is proposed.

Hypothesis 11 (H11): Perceived intelligence is positively related to continuation intention to use chatbot service interactions

Chandler and Schwarz (2010) identified that consumers were less willing to replace them when associated with anthropomorphic figures. The authors asserted that consumers tend to be possessed with the human-like characteristics present with the anthropomorphic conditions, which eventually can build loyalty with the brand. Service chatbots employ different names, tags, avatars, emojis, etc., during the conversation with the users. By applying Chandler and Schwarz (2010) study, users may get induced to the characters present in the chatbots. Thus, this can lead users to continue with service chatbots. The human stance present in anthropomorphic chatbots can induce users to feel more engaged as in human conditions, thus resulting to long term associations. However, these all remain as hypotheses which warrant further investigation. From the above discussion, the following hypothesis is proposed.

Hypothesis 12 (H12): Perceived anthropomorphism is positively related to continuation intention to use chatbot service interactions

3.5. Attitude and continuation intention

Attitude explains the positive or negative disposition towards a person, object or situation. Davis (1989, p. 984) defines attitude as "*the degree of a person's positive or negative feelings about performing a target behaviour*". Previous research has found a significant relationship between attitude and continuation intention (Hamari and Koivisto, 2015; Payne et al., 2018). Users tend to develop their continuing behaviour based on the disposition set on a technology (Wu and Chen, 2017). The same principle can extend to chatbot services. Thus, the following hypothesis is proposed.

Hypothesis 13 (H13): Attitude is positively related to continuation intention to use chatbot service interactions

3.6. Moderating role of social self-efficacy

Research in AI-based systems has ascertained that the absence of social elements can be a major limitation for AI-based systems (Yang et al., 2019). However, does it create an impact on the system? – a significant question that ponders answers from different applications. Notably, the possibility of a social element penetrating through the gates of intelligence in an AI system depends on user characteristics (Duan et al., 2019). People with higher social self-efficacy expect social interaction in a defined system (Smith and Betz, 2000), but this is a challenging factor in technology-based services. The user factors (performance expectancy, effort expectancy, facilitating conditions, and social influence) may positively build continuation intention to use chatbots in services. However, the expectation of the social element in the system can negatively impact the existing relationship. Shareef et al. (2021) proposed that social expectations in IS system can hamper system usage. The same proposition is possible when considering the continuing intention among the users. Service chatbots can provide multidimensional functions that improve the attitude and enable a continuing intention, but the same cannot satisfy social interaction. The evolution of services marketing is set from human associations (Zeithaml et al., 1985). The present technology and AI-based chatbot service factors question the evolutionary paradigm. The system factors (perceived intelligence and perceived anthropomorphism) are present across most AI applications (Bartneck et al., 2009b). The service chatbots incorporate similar features that can develop a positive attitude. The same does not guarantee social interaction. Given the above discussion, the following hypotheses proposes that high social self-efficacy may hamper the relationship between user and system factors to continuation intention.

Hypothesis 13a to 13f: Social self-efficacy negatively moderates the relationships proposed in H7 to H12

4. Methodology

4.1. Research design, procedure, and participants

The present study follows a single cross-sectional design with data collected using a survey methodology. The survey data was collected from 420 users who have previous experience engaging with chatbots in any pre-purchase, purchase, or post-purchase service interactions. The research used a non-probabilistic design to conduct the survey. The data was collected from the participants of six online conferences conducted in India. The conferences entailed broad themes connected to changing technology scenarios in services, AI and services integration, and commercial technology developments. These conferences were chosen to ensure the survey participants had sufficient knowledge regarding chatbots. The conference had more than 1500 participants, of which 1115 participants showed interest in participating in the survey. Before the survey, two screening questions were used to identify the representative sample among the 1115 participants: 1. Do you have adequate knowledge about using chatbots in service interactions (yes/no); 2. Are you a frequent user of chatbots in any service interactions (yes/no)? Overall, a total of 786 participants answered "Yes" to both questions, thus being found eligible to participate in this study. Of the 786 participants, 446 completed the survey; finally, 420 eligible response was considered for this study. The data collection extended for 55 days, and the data collected in the first 15 days was compared with the data collected in the last 15 days to identify the presence of non-response bias (Balakrishnan and Dwivedi, 2021b). The results of t test showed that there is no significant mean difference between the two-time intervals.

4.2. Instrument and measures

The survey instrument consisted of three parts. The first part of the questionnaire consisted of two questions; (1) Which service you have availed with chatbot the most? _________ (open-ended question), (2) Where you have used the chatbot the most __________? (pre-purchase/information search, purchase stage, post-purchase stage). The second part of the questionnaire consisted of study constructs measuring the study hypotheses derived from previous studies. The scales of performance expectancy, effort expectancy, facilitating conditions, and social influence is derived from previous studies (Venkatesh et al., 2003; Venkatesh et al., 2012; Slade et al., 2015). The scale of perceived intelligence and perceived anthropomorphism is derived from two studies (Bartneck et al., 2009a; Balakrishnan and Dwivedi, 2021b). The scale for attitude, continuation intention, and social self-efficacy is derived from Balakrishnan and Dwivedi (2021b), Ashfaq et al. (2020), and Sherer et al. (1982), respectively. The third part of the questionnaire consisted of social-demographic information such as; gender, age group, educational qualification, and occupation, which are measured as a categorical variable. All the measurement items are measured in seven-point (7 – Very Strongly Agree to 1- Very Strongly Disagree). The detailed information on the measurement items of the construct is given in Appendix A

4.3. Analysis

The study used a two-step structural equation modelling technique to investigate the proposed model. We first employed confirmatory factor analysis (CFA) to confirm the reliability, content validity, convergent validity, and discriminant validity requirements. As a part of CFA analysis, we performed common method bias test (CMB) to test the data is free from any measurement bias. After confirming validity and CMB requirements, structural equation modelling was used to test the proposed hypotheses. Maximum likelihood method (MLM) is used to estimate the model. Following the direct paths, the moderation effect of social self-efficacy is tested in the model. For all the estimation purposes, we used IBM SPSS and AMOS 26. Finally, to investigate the control variables, the multigroup analysis is performed to understand the hypotheses difference among the gender (male/female) and age (young/old) groups. To operationalise the variable age, we divided the sample into two groups; young and old from the inputs of the research by Plecher (2020), which stated that the Indian median age as of 2020 can be estimated to be 28.4 years, we divided the age group below 28 years as young and above 28 years as an older sample. A similar methodology is followed in the previous studies (Balakrishnan et al. 2021; Khan et al., 2020). Prior to estimating the relationships in multigroup analysis, multigroup CFA was first performed to verify the unidimensionality and convergent validity of the constructs (Anderson and Gerbing, 1988).

Table 1: Socio-demographic characteristics of the sample

	Variables	**Characteristics**	**Count**	**%**
CE	Gender	Male	238	56.66
		Female	182	43.34
CE	Age group	Young (19 to 28 years)	255	60.72
		Old (29 to 55 years)	165	39.28
CE	Education Qualification	Graduate	56	13.33
		Post Graduate	153	36.43
		PhD	211	50.24
CE	Occupation	Students	126	30.00
		Working Professional	231	55.00
		Business	63	15.00
OE	Which service you have availed with chatbot the most? _________	Service complaints	212	50.47
		Bookings and Purchases	115	27.38
		Information search	51	12.15
		Contact enquiries	30	7.14
		Conversation	12	2.86
CE	Where you have used the chatbot the most _______________ (pre-purchase/information search, purchase stage, post-purchase stage)	Pre-purchase activities	93	22.15
		Purchase activities	115	27.38
		Post-purchase activities	212	50.47
CE denotes Close Ended Questions; OE denotes Open-Ended Questions				

Table 2: Results of Measurement Model (CFA)						
Construct	**Items**	**Mean**	**Std. Dev**	**Factor**	**CA**	**AVE**
Performance Expectancy	PE1	4.72	1.750	0.953^{***}	0.965	0.904
	PE2	4.80	1.734	0.936^{***}		
	PE3	4.79	1.784	0.963^{***}		
Effort Expectancy	EE1	4.73	1.773	0.928^{***}	0.936	0.877
	EE2	4.72	1.768	0.945^{***}		
	EE3	4.84	1.754	0.956^{***}		
	EE4	4.57	1.625	0.917^{***}		
Social Influence	SI1	4.65	1.707	0.849^{***}	0.818	0.785
	SI2	4.66	1.858	0.878^{***}		
	SI3	4.53	2.013	0.939^{***}		
Facilitating Conditions	FC1	4.19	1.865	0.938^{***}	0.807	0.749
	FC2	4.57	1.780	0.919^{***}		
	FC3	4.34	1.786	0.872^{***}		
	FC4	4.27	1.775	0.888^{***}		
Perceived Intelligence	PI1	4.79	2.024	0.901^{***}	0.901	0.886
	PI2	4.76	1.898	0.915^{***}		
	PI3	4.68	1.916	0.936^{***}		
	PI4	4.65	1.832	0.898^{***}		
	PI5	4.60	1.821	0.918^{***}		
Perceived Anthropomorphism	PA1	5.09	1.934	0.963^{***}	0.843	0.908
	PA2	4.98	1.897	0.942^{***}		
	PA3	4.89	1.851	0.938^{***}		
	PA4	4.80	1.831	0.920^{***}		
	PA5	4.83	1.788	0.876^{***}		
Social Self-Efficacy	SSE1	4.01	2.043	0.925^{***}	0.876	0.769
	SSE2	3.62	1.902	0.811^{***}		
	SSE3	4.20	2.083	0.938^{***}		
	SSE4	3.78	1.875	0.919^{***}		
	SSE5	3.92	1.912	0.811^{***}		
	SSE6	4.67	1.672	0.915^{***}		
Attitude	Att1	4.22	1.811	0.927^{***}	0.814	0.837
	Att2	4.25	1.820	0.911^{***}		
	Att3	4.18	1.770	0.906^{***}		
Continuation Intention	CI1	4.44	1.692	0.944^{***}	0.918	0.874
	CI2	4.58	1.696	0.916^{***}		
	CI3	4.55	1.773	0.945^{***}		

Note: CA represents "Cronbach's Alpha"; AVE represents "Average Variance Extracted"; CFA Fit indices: $\varkappa 2/df = 2.83$; GFI = 0.922, CFI = 0.945, (Good fit>0.9); RMSEA=0.057 (Good fit <0.06); Note:

5. Results

5.1. Respondents demographic characteristics

The sample consisted of 56.66% male and 43.34% female participants, which confirmed that the sample offered a largely representative gender distribution. The age group is also diversified among the young (60.72%) and old (39.28%) population. The same diversified pattern can be observed with educational qualifications and occupation. The detailed socio-demographic details of the same are provided in Table 1. Regarding the open-ended question on "*which service you have availed with chatbot the most*", 50.47 % of the sample has that they have used the chatbots for service complaints, followed by bookings and purchases (27.38%), information search (12.15%), contact enquiries (7.14%), and conversation (2.86%). The same results also indicated that 22.15% of the sample used chatbots for the pre-purchase stage, 27.38% during purchase, and 212 during the post-purchase stage

5.2. Measurement model and CMB

The confirmatory factor analysis results confirmed the reliability and validity requirements of the model constructs, permitting to proceed with structural equation modelling. Table 2 and Table 3 shows the Cronbach's alpha and composite reliability value above 0.75, which confirms the scale is reliable and internally consistent (Portney and Watkins, 2000). Table 2 shows the factor loadings above 0.60, which confirmed the content validity requirements (Nunnally, 1978). In the same table, the AVE scores can be found above 0.50, which confirms the convergent validity requirements (Fornell and Larcker, 1981). The inter-correlation and √AVE are given in Table 3. The table shows that the diagonal (√AVE) of respective constructs is more than the inter-correlation established with the other constructs. The result also confirms that the construct satisfies the requirements of discriminant validity (Fornell and Larcker, 1981). All validity requirements met the thresholds proposed by Bagozzi et al. (1991) and Fornell and Larcker (1981). The fit of the model is presented in the footnote of Table 2. It can be observed that the fit indices satisfied and demonstrated good fit in the measurement model as suggested by previous studies (Kline, 1998; Byrne, 2010; Hair et al., 2012).

Table 3: Inter-construct correlations and √AVE values										
Variable	**CR**	**CI**	**PE**	**EE**	**SI**	**FC**	**PI**	**PA**	**ATT**	**SSE**
CI	0.916	**0.935**								
PE	0.966	0.603	**0.951**							
EE	0.936	0.655	0.872	**0.937**						
SI	0.815	0.632	0.857	0.786	**0.886**					
FC	0.807	0.233	0.279	0.363	0.402	**0.865**				
PI	0.902	0.618	0.508	0.604	0.603	0.278	**0.941**			
PA	0.844	0.617	0.601	0.668	0.673	0.292	0.724	**0.953**		
ATT	0.814	0.680	0.686	0.728	0.710	0.291	0.604	0.683	**0.915**	
SSE	0.878	0.401	0.282	0.332	0.340	0.315	0.392	0.458	0.494	**0.877**

The values in the diagonal of the table represent the √AVE values

Explanations: CR = Composite Reliability; CI = Continuation Intention; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; PI = Perceived Intelligence; PA = Perceived Anthropomorphism; ATT = Attitude; SSE = Social Self-Efficacy

Further to the measurement model (CFA), the common method bias (CMB; Podsakoff et al., 2003) analysis is performed to understand the data is free from common method bias. To test the same, the standardised estimates of the CLF (common latent factor) model is compared with the non-CLF model to check that the differences in factor loadings are less than 0.05. The results highlighted that the difference ranged from 0.012 to 0.036, thus satisfying the primary condition of CLF to confirm that the data is free from CMB issues (MacKenzie and Podsakoff, 2012).

Table 4: Standardised estimates of the proposed model					
Hypotheses	**Exogenous Variable**	**Endogeno us**	**Model 1 Coefficien**	**Model 2 Coefficien**	**r^2**
Hypothesis 1	Performance Expectancy	Attitude	0.283**	0.281**	0.421
Hypothesis 2	Effort Expectancy		0.355**	0.354**	
Hypothesis 3	Facilitating Conditions				
Hypothesis 4	Social Influence		0.212**	0.209**	
Hypothesis 5	Perceived Intelligence		0.411**	0.386**	
Hypothesis 6	Perceived Anthropomorphism		0.382**	0.374**	
Hypothesis 7	Performance Expectancy	Continuation Intention	0.207**	0.178**	0.342
Hypothesis 8	Effort Expectancy		0.282**	0.246**	
Hypothesis 9	Facilitating Conditions				
Hypothesis	Social Influence			0.056^{ns}	
Hypothesis	Perceived Intelligence		0.384**	0.194**	
Hypothesis	Perceived Anthropomorphism		0.336**	0.151**	
Hypothesis	Attitude		0.454**	0.388**	
Hypothesis	Performance Expectancy x Social Self-			-0.098^{ns}	
Hypothesis	Effort Expectancy x Social Self-Efficacy			-0.087^{ns}	
Hypothesis	Facilitating Conditions x Social Self-			0.016^{ns}	
Hypothesis	Social Influence x Social Self-Efficacy			-0.059^{ns}	
Hypothesis	Perceived Intelligence x Social Self-Efficacy			-	
Hypothesis	Perceived Anthropomorphism x Social Self-			-	
Notes: *** represent values significant at 99% confidence level; ** represent values significant at 95% confidence level.					

5.3. Structural model

Table 4 shows the results of standardised estimates of model 1 (without moderating effect of social-self efficacy) and model 2 (with moderating effect of social self-efficacy). Regarding model 1, the hypotheses connecting user factors of meta-UTAUT to attitude were found to be significant, with the estimate between facilitating conditions and attitude is found to be lesser compared to the other three hypotheses. The system factors (perceived intelligence and perceived anthropomorphism) to attitude showed improved results than the user factors. The r^2 for attitude is 0.421, which demonstrated that the attitude exhibited 42.1% of the variance in the model. Hypotheses 7 to 13 examined the relationship of the user, system, and attitude to continuation intention. Social influence is insignificant in building the continuation intention of the chatbots, and the remaining hypotheses were found to be significant. Of which, the variables perceived intelligence, and perceived anthropomorphism is found to be highly significant. The r^2 of continuation intention is 0.342, which explains that the variable explains

34.2% of the total variance. Notably, the relationship between attitude and continuation intention is higher than any other investigated hypotheses.

Table 5: Multi-group analysis results

			Age			Gender		
Constructs			Young	Old	z-score	Male	Female	z-score
Endogenous		**Exogenous Construct**	**Estimate**	**Estimate**		**Estimate**	**Estimate**	
Attitude	←	Performance	0.214***	0.312***	-1.898**	0.115^{ns}	0.126**	-0.118^{ns}
	←	Effort Expectancy	0.187**	0.265***	-1.587**	0.121**	0.174**	-0.668^{ns}
	←	Facilitating Conditions	0.098^{ns}	0.236***	-3.135***	0.186**	0.212***	-0.554^{ns}
	←	Social Influence	0.154**	0.167**	-0.141^{ns}	0.152**	0.311***	-2.256***
	←	Perceived Intelligence	0.248***	0.312***	-0.783^{ns}	0.187**	0.228***	-0.823^{ns}
	←	Perceived	0.212***	0.098	2.868***	-0.036^{ns}	0.110^{ns}	-1.887**
Continuation Intention	←	Performance	0.187***	0.227***	-0.324^{ns}	0.184**	0.157**	0.548^{ns}
	←	Effort Expectancy	0.227***	0.235***	-0.127^{ns}	0.214***	0.286***	-1.105^{ns}
	←	Facilitating Conditions	0.174**	0.156**	0.215^{ns}	0.175**	0.142**	0.417^{ns}
	←	Social Influence	0.104^{ns}	0.187**	-1.475^{ns}	0.114^{ns}	0.286***	-3.865***
	←	Perceived Intelligence	0.215***	0.256***	-0.528^{ns}	0.247***	0.288***	-0.774^{ns}
	←	Perceived	0.186**	0.124**	0.678^{ns}	0.312***	0.198**	2.143***
	←	Attitude	0.347***	0.272***	1.988**	0.278***	0.336***	-1.027^{ns}

Note: *** represent values significant at 99% confidence level; ** represent values significant at 95% confidence

5.4. Moderating effect and the control variables

The model 2 results showed the impact of social self-efficacy as a moderator. There is no considerable change in hypotheses 1 to 6 because of the moderating variable, but there is considerable change in hypotheses 7 to 12. As shown in Table 4, the interaction effect of social self-efficacy with performance expectancy, effort expectancy, facilitating conditions, and social influence did not affect continuation intention. However, the interaction effect of social self-efficacy with perceived intelligence and perceived anthropomorphism had a negative effect on continuation intention. This result shows that a higher social self-efficacy can dampen the relationship of perceived intelligence and perceived anthropomorphism to continuation intention. Table 5 shows the multigroup analysis results. In the case of age, the results indicate the relationship between facilitating conditions to attitude, and the remaining paths were not significantly different at a 99% confidence level. In the case of gender, except for the relationships between social influence to attitude, social influence to continuation intention, and perceived anthropomorphism to continuation intention, the remaining paths were not significant at a 99% confidence level. In case of the age groups, the coefficients of the relationships are higher for old age sample compared to the young age sample. However, there is no significant change in the coefficients. In case of gender, the coefficients of the female sample are relatively higher than the male sample for most of the relationships. However, there is no significant change effect found.

6. Discussion

This study used the meta-UTAUT framework to investigate the impact of user factors and system factors on attitude and continuation intention on using chatbots in services. Notably, the study also introduced social self-efficacy as a moderator in the proposed relationships of 12 hypotheses. H1 to H6 investigated the role of user and system factors to attitude, H7 to H12 investigated the role of these factors towards continuation intention, H13 investigated the relationship of attitude to continuation intention. H12a to H12f investigated the moderating effect of social self-efficacy specific to the relationship proposed from H7 to H12. The results of these hypotheses will be discussed in the following sections, focusing on how these models and results have provided meaning to the existing and proposed theoretical knowledge.

The results of hypotheses 1 to 4 showed that performance expectancy, effort expectancy, facilitating conditions, and social influence could lead to a positive attitude towards chatbot services. The results also conform to the Meta-UTAUT framework in which Dwivedi et al. (2019) found that all four variables significantly impact attitude. However, the meta-UTAUT framework found performance expectancy as the most significant variable, and the research found effort expectancy as a more significant variable. This result demonstrates how these chatbots are emerging compared to the existing information system. Hypotheses 5 and 6 demonstrated that perceived anthropomorphism and perceived intelligence could more significantly build attitude. The results are novel in the context of chatbots. Previous research has supported that system intelligence can build a favourable behaviour in information systems (Duan et al., 2019). This research confirms such findings. Marketing research has supported that anthropomorphic characters can build a positive attitude (Kim et al., 2020); the study results extend understanding in the context of chatbots.

The results of hypotheses 7 to 9 infer that performance expectancy, effort expectancy, and facilitating conditions can build the continuation intention of chatbots in services. Previous research has found that these user factors contribute to continuation intention (Tam et al., 2020). However, showing the insignificant result of social influence to the continuation (h10) is a new finding. Previous research has supported that a highly dynamic IS is more cognitive based and cannot be socially involved (Gupta et al., 2018). The result of h10 supports this theory. The results of hypotheses 11 and 12 indicate the significant positive relationship between perceived intelligence and perceived anthropomorphism to continuation intention.

Previous research has supported AI systems can induce continuing intention (Ashfaq et al., 2020).

Given that intelligence has become an identity of AI systems, the results conform with Ashfaq et al. (2020). In the case of perceived anthropomorphism, there is no exact theory to confirm the finding. However, Chang et al. (2018) found that social robots with human-like conditions extend continuing engagement among the users. By intersecting the present study results with Chang et al. (2018), it is apparent that anthropomorphism does create a continuing long-term association in a given AI-based system. Previous studies support the relationship of attitude in IS to continuing intention, supporting the results of hypothesis 13.

Hypotheses 12a to 12f investigated the moderating role of social self-efficacy in the relationship proposed in hypotheses 7 to 12. The results indicated that social self-efficacy did not significantly moderate the relationship of user factors to continuing intention. However, the relationship between system factors (perceived intelligence and perceived anthropomorphism) to continuing intention is negatively moderated by social self-efficacy. There is no previous research that has investigated similar hypotheses. The user factors (meta-UTAUT) denotes the perceived benefit that a user can attain by using the system, but the system demands interaction and understandability within the scope of the system. Thus, in service chatbots, perceived intelligence and anthropomorphism are perceived as non-social elements. Such perception may be due to the system intelligent archetypes are perceived against the social expectations (Elbanna et al., 2020). While using age as a control variable, the facilitating conditions and perceived anthropomorphism to attitude differ across the young and old population. Previous research has supported that young and old may expect different IS parameters and system architecture (Morris and Venkatesh, 2000). In addition, the human-like conditions are more significantly accepted by young than old (Gupta and Jain, 2019). These results support this ideology. In the case of gender, social influence is significantly higher with female groups both while formulating relationships with attitude and continuing intention. Previous theories have supported that females are more prone to social influence in the information sharing context (Raman, 2020). Thus the results fall into the region of the theories mentioned above.

6.1. Theoretical implications

This research adds multiple values to the existing frameworks and literature; (1) The meta-UTAUT framework (Dwivedi et al., 2019) is extended with system factors (perceived intelligence and perceived anthropomorphism). (2) Social self-efficacy is introduced as a moderating factor in the meta-UTAUT framework. (3) As proposed by the meta-UTAUT framework, this study stresses the relationship between attitude and continuation intention in service chatbots. (4) The model provides a holistic outlook on how these relationships differ across age and gender.

Firstly, previous research has extended meta-UTAUT with personal innovativeness, anxiety, trust, and grievance redressal (Patil et al., 2020); compatibility, CRM Quality, and CRM satisfaction (Chatterjee et al., 2021); hedonic motivation, self-efficacy (Tamilmani et al., 2020); and awareness (Bu et al., 2021). This study has extended the meta-UTAUT framework with perceived intelligence and perceived anthropomorphism. Compared to previous extended meta-UTAUT, this framework provides holistic understanding from AI-based systems and chatbots. Thus, the proposed system factors extend the available knowledge in the meta-UTAUT framework, AI-based systems, and chatbot-based services. Secondly, research investigating technology-based services has passed on the dilemma emphasising the importance of satisfying social expectations (Lu et al., 2020). By introducing social self-efficacy as a moderator, this study has answered that social expectations may not affect the user factors, but they do negatively impact the system factors. Previous studies have investigated the moderating role of self-efficacy in technology adoption (Huang and Ren, 2020). This study extended the understanding from the social self-efficacy context. The results will provide more meaningful insights into social cognitive theories, especially in the context of services and chatbots. Moreover, the importance of social expectations against the system intelligence is emphasised from the study results. The results have also surfaced a foundation for concepts and theories such as; feeling economy (Huang et al., 2019), human-machine interactions (Balakrishnan and Dwivedi, 2021a), and machine learning (Duan et al. 2019) to be further explored through the lens of the system factors.

Thirdly, the study has emphasised the role of attitude and continuation intention. Though the relationship is well established, most IS research has connected user factors with attitude or behavioural intention. Thus, the attitude and continuation intention results have reiterated the importance of creating a favourable disposition in service chatbots. Fourthly, the model will provide a more comprehensive understanding of the services research, especially emphasising system factors. So far, the literature in technology-based services research has explored chiefly the frameworks formulated from the base of TAM and UTAUT, and this research has moved ahead to extend the meta-UTAUT framework. In addition, the investigated framework has contrasted the results from the age and gender point of view. These results will allow academics to decode the existing literature with the insights provided here, especially using the control variables.

6.2. Practical implications

The study results lend valuable insights to IS and service managers through the following implications; (1) the importance of considering the user and system factors while designing service chatbots, (2) the importance of integrating more social aspects in the service chatbots interaction, (3) employing social elements in the intelligence and anthropomorphism as perceived by the user.

From the results, it is evident that system factors are more related to attitude and continuation intention than user factors. This result also enhances the discussion on the possibilities of upscaling the effect of intelligence and imparting more anthropomorphic conditions. Prior research has discussed various ways in improvising intelligent frameworks and anthropomorphic features in AI-based robots (Blut et al., 2021). Given that robots and chatbots are similar in terms of AI integration, service marketers, with the help of IS managers, can revisit the robotic literature and other intelligent IS frameworks to optimise improved intelligence and anthropomorphism. However, it is also equally important to respond to the social expectations in chatbots. In the present scenario, the intelligence or anthropomorphism provided in AI-based systems are not effective enough to replace humanistic aspects (Aladwani and Dwivedi, 2018). Pelau et al. (2021) suggest implications to incorporate more human-like characteristics. The same can guide IS managers and service marketers to develop chatbots with social elements.

7. Conclusions, limitations, & future research directions

This study investigated the effect of user factors and system factors on attitudes towards service chatbots and continuation intention to use chatbots in services. It is conclusive that system factors contribute more to building attitudes and continuation intention towards chatbots. Furthermore, users with higher social self-efficacy tend to interact negatively with perceived intelligence and anthropomorphism to further hamper the relationship with continuation intention. Overall, the study emphasises the importance of system factors and the need to incorporate social factors in the chatbot to build more service continuation intention. The study results will contribute and extend the available knowledge in the meta-UTAUT, social-cognitive theory, and emerging literature in AI based services. Furthermore, the study can operate meaningful insights to the service managers. The study used a cross-section research design, an experimental design with appropriate stimuli level measuring social element, anthropomorphism level, and intelligence to provide a more comprehensive understanding. This study used only two major factors underlying AI technology, and future studies can extend the meta-UTAUT framework with other system factors such as; system likeability, animacy, and efficiency. Future studies can seek (1) to incorporate the model in other relevant industries such as; tourism, social media, etc. (2) to test the indirect and interaction effects of other social factors which fall under the scope of social cognitive theory (3) an exclusive investigation on any of the service stages such as; pre-purchase, purchase, and post-purchase stage.

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Appendix A: Items used in construct measurement (7-point scale)		
Construct	**Scale**	
Performance Expectancy	I would find chatbot based services useful in my daily life.	Venkatesh et al. (2003); Venkatesh et al. (2012); Slade et al. (2015)
	Using chatbot would help me accomplish things more quickly.	
	Using chatbot for services might increase my productivity.	
Effort Expectancy	Learning how to use chatbot for services would be easy for me.	
	My interaction with chatbot during services would be clear and understandable.	
	I would find chatbot based services easy to use.	
	It would be easy for me to become skillful at using chatbot.	
Social Influence	People who are important to me think that I should use chatbot in services.	
	People who influence my behavior think that I should use chatbot in services.	
	People whose opinions I value prefer that I use chatbot in services.	
Facilitating Conditions	Chatbot provide have the resources necessary for service use.	
	I have the knowledge necessary to use the chatbot for service use.	
	Chatbot are more compatible for service use.	
	Chatbot have service assistance in case of any system difficulties.	
Perceived Intelligence	Chatbot are competent in providing services.	Bartneck et al. (2009a); Balakrishnan and Dwivedi, (2021b)
	Chatbot are knowledgeable during service interactions.	
	Chatbot exhibit responsibility during service interactions.	
	Chatbot have intelligent functions concerned with services.	
	Chatbot are sensible during service replies.	
Perceived Anthropomorphism	Chatbot are natural; I do not feel fake about it.	Bartneck et al. (2009a);
	Chatbot are more humanlike.	
	Chatbot are conscious of their actions.	

	Chatbot feel lifelike and not artificial.	Balakrishnan and Dwivedi, (2021b)
	Chatbot are elegant in engaging.	
Social Self-Efficacy	It is not difficult for me to make new friends.	Sherer et al. (1982)
	If I see someone I would like to meet, I go to the person instead of waiting for him or her to come to me.	
	If I meet someone interesting who is hard to make friends with, I'll soon start trying to make friends with that person.	
	When I'm trying to become friends with someone who seems uninterested at first, I don't give up easily.	
	I handle myself well in social gathering.	
	I have acquired my friends through my personal abilities at making friends.	
Attitude towards chatbot	I like using chatbot for services	Balakrishnan and Dwivedi (2021b)
	I feel good about using chatbot for services	
	Overall, my attitude towards using chatbot for services is favourable	
Continuing Intention	I intend to continue using this chatbot based services in the future	Ashfaq et al. (2020)
	I will always try to use this chatbot based services in my daily life	
	I will strongly recommend others to use chatbot for services	

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